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Borrower Expectations and Mortgage Performance: Evidence from the COVID-19 Pandemic

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Abstract

We exploit plausibly exogenous fluctuations in borrower house price and job loss expectations to estimate the causal effect of expectations on loan performance. Borrowers whose house price expectations fell early in 2020 were more likely to enter forbearance, but then quickly exited as house prices continued to appreciate. However, borrowers who expected job loss entered and remained in forbearance throughout the weak labor market. We also find that house price changes in a borrower's social network affect their expectations as much as local house price appreciation, and these expectations formed at origination affect future leverage and debt service ratios. In sum, our results are consistent with models of adaptive expectations where borrowers adjust beliefs gradually and, in turn, affect aggregate activity in the mortgage market.

Keywords: Behavioral Economics · Employment · Forbearance · Expectations.

JEL Classification: E21, E32, G41, G51, R31.

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1 Introduction

There is mounting microeconomic evidence that expectations play a substantial role in influencing not only aggregate economic activity, but also, and more specifically, housing price dynamics (Piazzesi and Schneider, 2009; Burnside et al., 2016; Glaeser and Nathanson, 2017; Kaplan et al., 2020), loan terms (Geanakoplos, 2010; Brueckner et al., 2012, 2016; Bailey et al., 2019), and homeownership (Bailey et al., 2018; Armona et al., 2019).[1] One of the channels by which economists believe expectations influence booms and busts in the housing market is through the proportion of optimistic agents that respond to changing collateral-lending standards: looser standards can lead optimistic agents to increase their leverage, leading to an unsustainable increase in housing prices (Geanakoplos, 2010).[2] A large body of research has subsequently emerged studying the role of macro-prudential regulation to support the stability of banks even when asset values deviate from their fundamentals.

However, much less is known about the underlying borrowers who might be over optimistic or pessimistic about house prices, and how these expectations influence loan performance at a micro level.[3] Unfortunately, answering that question has been empirically challenging because of unobserved heterogeneity: borrower expectations may correlate with mortgage selection for other reasons, such as preferences and ability. To overcome classic endogeneity problems, we draw on novel, longitudinal, and newly-released data from the National Mortgage Database® (NMDB) and the National Survey of Mortgage Originations (NSMO) between 2012 and 2022 to quantify how changing borrower expectations drove execution of forbearance options during the COVID-19 pandemic. We subsequently examine the determinants of these expectations as a function of borrower characteristics, local and network shocks, and the national economic environment. Finally, we examine how expectations formed at origination shape future leverage and debt burdens, conditional on controls.

The first part of the paper introduces the institutional background about forbearance and

[1] An alternative view is that the 2007-08 housing bust was the result of a lack of regulation and expansion in new financial products; see, for example, Parlour and Plantin (2008) and Chemla and Hennessy (2014).

[2] In these models, credit-constrained borrowers need collateral because of information asymmetries and incomplete contracts (Kiyotaki and Moore, 1997; Bernanke et al., 1999; Rampini and Viswanathan, 2010).

[3] Some patterns are, however, clear. For example, conditional on selecting into an adjustable rate mortgage (ARM), holders are more likely to default if economic conditions are unfavorable, although borrowers with higher unconditional probabilities of early termination are more likely to choose fixed rate mortgages (Capone and Cunningham, 1992). Nonetheless, there is substantial heterogeneity among holders of ARMs that vary in their term lengths (Makridis and Ohlrogge, 2022). Furthermore, overly optimistic house price expectations can fuel subprime lending, creating a positive feedback loop (Brueckner et al., 2012, 2016).

augments a stylized three-period double-trigger model in the tradition of Foote et al. (2008a) with adaptive house price expectations and expected future unemployment. Our model predicts that mortgage performance is a function of expectations about house price appreciation and labor market outcomes. As the national state of the economy changes over time, borrowers update their individual beliefs. In a deteriorating economy, those borrowers who previously had been the most optimistic about house prices or were less certain about future employment experience a higher propensity to enter forbearance.

The second part of the paper presents the merged NMDB and NSMO data and documents some stylized facts. First, during the initial months of the pandemic as national house price expectations fell, forbearance uptake was higher among borrowers who expected high levels of house price appreciation at loan origination, even among loans that were originated before the pandemic. Second, as house prices were observed to appreciate and expectations rebounded, appreciation-optimists exited forbearance at higher rates than the general population. Third, forbearance uptake was higher among borrowers who expected to be laid off or become unemployed soon after loan origination. In contrast to the housing market, the labor market substantially cooled, with nearly 70 million cumulative initial unemployment insurance claims in 2020 according to the U.S. Department of Labor. Accordingly, these households entering forbearance remained in forbearance at high levels throughout 2020 and 2021. Combined, these results suggest both changing expectations and actual economic events can drive mortgage option execution, and how each can differentially affect different types of borrowers depending on measures of initial beliefs.

The third part of the paper presents our baseline empirical model of the effects of changing expectations on forbearance, consistent with theory. We exploit within-borrower variation by tracing out monthly forbearance status as a function of divergence between expectations at the time of origination and monthly national sentiment about the economy or the labor market. Borrowers with more optimistic house price expectations at the time of origination experienced higher rates of forbearance uptake as national price expectations decreased. Similarly, borrowers with less optimistic expectations about future employment at the time of origination experienced higher rates of forbearance uptake as local unemployment rates increased. Crucially, we are able to identify the effects of expectations on mortgage performance holding constant borrower-level effects, both observable and unobservable. We replicate these results without borrower fixed effects, instead including a comprehensive set of borrower and loan controls and origination fixed effects, to understand how borrower-level attributes affect forbearance uptake, conditional on expectations. Our results are robust to focusing on a pre-COVID-19 sample, alternative empirical specifications, and varying selection concerns.

The fourth part of the paper examines the determinants of house price expectations as a function of borrower characteristics and local and network shocks. In addition to realized house price appreciation and the unemployment rate within a county, we also create a network measure of these shocks using the Social Connectedness Index (SCI) from Bailey et al. (2018) that reflects a weighted average of house price growth in all connected counties with weights determined by the number of friendship ties with the corresponding county. We show that these SCI-weighted house price and unemployment rate shocks are just as important for shifting expectations as the realized local shocks. Finally, we show expectations are associated with higher leverage and debt service payment ratios.

Our paper builds on a large literature relating the effects of expectations on real economic activity. Although there has been a recognition since at least Keynes (1936) that expectations matter for explaining business cycle fluctuations, isolating plausibly exogenous variation in micro-data has been difficult. However, an emerging body of work now points towards a causal effect of individuals' economic sentiment on consumption (Gillitzer and Prasad, 2018; Benhabib and Spiegel, 2019; Makridis, 2022). Others have demonstrated how expectations of future house price appreciation are important determinants of house price dynamics (Case and Shiller, 1988; Glaeser and Nathanson, 2015; Adelino et al., 2018; Kaplan et al., 2020), choices of loan terms (Geanakoplos, 2010; Brueckner et al., 2012, 2016; Bailey et al., 2019), and portfolio decisions (Armona et al., 2019). We show that expectations influence mortgage performance as measured by forbearance and largely as a function of leverage choices at the time of origination. This contributes to a theoretical literature on the importance of leverage choices for aggregate fluctuations (Geanakoplos, 2010; Geanakoplos and Wang, 2020).

Our paper is also related with a literature on the effects of foreclosure mitigation policies (Eberly and Krishnamurthy, 2014; Piskorski and Seru, 2018; Campbell et al., 2020). While there is some evidence of strategic motives for default (Guiso et al., 2013), improvements in measurement and the scale of data suggest that strategic default, in contrast to the inability to pay, is not prevalent. For example, Gerardi et al. (2017) find that a 10% decline in residual income leads to a 1.1-2.5pp rise in the probability of default. Our paper is most closely related with Cherry et al. (2021) who document a surge in forbearance rates, concentrated in mortgage and student debt, over the COVID-19 pandemic. Moreover, they exploit variation in the conforming loan balance limits to isolate the causal effect of forbearance, finding that it increases by about 25% for loans covered by the mandate. Though COVID-19 is an exogenous shock, moral hazard effects on debt relief are still a concern, as in loan renegotiation efforts (Piskorski and Tchistyi, 2010, 2011; Piskorski et al., 2010), especially because borrowers needed only to attest to hardship without need for verifying documentation. However, our link between forbearance and *ex ante* perceived unemployment risk should be reassuring that borrowers in need of forbearance did seem to receive it. In sum, our paper provides the first plausibly causal evidence linking borrower expectations with forbearance.

2 Background and Conceptual Framework

2.1 Institutional Background

"Forbearance" is an agreement between a loan servicer and a borrower not to take action in response to borrower delinquency of the terms of the loan. These agreements exist in normal times as loss-mitigation strategies for lenders and servicers during periods of hardship for a borrower. In response to the COVID-19 pandemic, first the FHFA on March 18, 2020 for Fannie Mae and Freddie Mac, and then the Coronavirus Aid, Relief, and Economic Security (CARES) Act, signed into law on March 27, 2020, for all "federally-backed" mortgages, expanded forbearance eligibility and codified a "consumer right to request forbearance" due to a COVID-19-related hardship (CARES Act, Section 4022). The CARES Act covered all federally-backed loans, defined as those purchased or securitized by Fannie Mae, Freddie Mac, FHA, VA, or FSA/RHS. Sections related to forbearance in the CARES Act are in force for the duration of the President's emergency declaration for the COVID-19 pandemic, which went into effect March 13, 2020.

The CARES Act stipulated that forbearance was guaranteed simply by a borrower fulfilling two conditions: submitting a request to the loan's servicer and affirming a financial hardship due to COVID-19. When in forbearance, scheduled payment amounts could accrue without any penalties, fees, reporting of delinquency to credit repositories, or fear of foreclosure. Loans that were current pre-CARES Act but went into forbearance were to be classified as current rather than delinquent (Section 4021), while loans that were delinquent pre-COVID or for non-COVID hardship-related reasons could not be foreclosed upon. Servicers of loans not covered by the CARES Act often volunteered to grant the same concessions as those mandated by the Act.

The initial forbearance term, as stipulated in the CARES Act, is up to 180 days followed by another 180 extension at the borrower's request, nearly a year in total. On February 25, 2021, the FHFA extended forbearance eligibility for Fannie Mae and Freddie Mac loans for another 6 months. Borrowers can continue making payments during the forbearance period and can cancel forbearance at will. Forbearance periods need not be continuous, however, and can be started, ended, and re-started so long as the total time in forbearance does not exceed these limits. Loans that are originated during the COVID-19 emergency continue to be subject to the forbearance and credit reporting flexibilities afforded by the CARES Act, though not the final 6-month extension afforded to Enterprise loans if they were originated after February 25, 2021.

2.2 A simple frictionless double-trigger model of forbearance

To help understand differences in forbearance behavior among eligible borrowers, we present a frictionless double-trigger mortgage options model with forbearance. We augment Foote et al. (2008b) by incorporating adaptive house price expectations and expected future unemployment so that current mortgage performance becomes a function of expectations about house price appreciation and labor market outcomes.

In our model, borrowers live for three periods, $t = \{0, 1, 2\}$. They inherit into period 1 expectations generated at loan origination, period 0, and face realizations of those outcomes and updated expectations in periods 1 and 2. We focus on forbearance option execution in period 1.[4] This period resembles one where the loan has existed for some time. However, expectations of future appreciation may have changed since the loan originated, and the borrower may have become unemployed. These factors can lead to forbearance or default behavior before negative appreciation has been realized. This period closely resembles March or April of 2020, just after the beginning of the COVID-19 lockdowns that resulted in the layoffs of millions of workers, and after households had, for a brief moment, become pessimistic about future appreciation. In this setting, we proceed.

[4]We do not consider factors relating loan origination and survival to expectations or other variables. A richer model such as one building on Brueckner et al. (2016) would include these processes. Nevertheless, the simple model presented here arrives at useful and intuitive predictions to help frame the empirical sections to come.

In period 1, there is an outstanding mortgage balance M_1 and the home is valued at P_1. There are two possible states of the world in period 2, "good" and "bad", with a house price P_2^G with probability α in the good state, and P_2^B with probability $(1-\alpha)$ in the bad state. In the bad state, the loan is underwater, $M_2 > P_2^B$ and the borrower defaults. In the good state the borrower sells the home.

Expectations of house price appreciation α for individual i are formed at loan origination, α_{i0}, and updated in period 1 based on expectations from national news α_1^N according to an adaptive expectations process.

$$\alpha_{i1} = \alpha_{i0} + \rho(\alpha_1^N - \alpha_{i0}) \tag{1}$$

Borrower i is fully employed in period 0 but has expectations of future unemployment β_{i0}. This borrower then faces a realization in period 1, where $E_0 b_i = \beta_i$, and both b and β are between 0 and 1, with 1 indicating total unemployment (no hours worked). These employment states give rise to financing costs in period 1 of $r + b_i r^U$, where r is the mortgage rate plus a spread r^U if the borrower is unemployed. The spread reflects additional borrowing needed to smooth consumption, higher perceived riskiness from lenders, and a higher discount rate due to greater marginal utility from current consumption (Foote et al., 2018).

The expected value of the mortgage in period 1 when making the scheduled mortgage payment *mpay* is as follows, where M_2 is the loan balance in period 2 under scheduled amortization and where the default (put) option allows us to substitute P_2^B for M_2 in the bad value state.

$$V_{i1}^M = mpay_1 + \frac{1}{1 + r + b_i r^U}\left[\alpha_{i1} M_2 + (1 - \alpha_{i1}) P_2^B\right] \tag{2}$$

The expected value of the mortgage under forbearance is calculated based on the deferred payments and the default option in period 2 plus some initial cost of entering forbearance in period 1. Added to M_2 is an an additional $(1+r)mpay_1$, the deferred mortgage payment (plus interest) that is paid in the good state. The cost of entering forbearance is $C_i^F = C^F + s_i$ where C^F are costs common to all borrowers, and s_i is an individual-specific cost.

$$V_{i1}^F = \frac{1}{1 + r + b_i r^U}\left[\alpha_{i1}(M_2 + (1+r)mpay_1) + (1 - \alpha_{i1}) P_2^B\right] + C_i^F \tag{3}$$

The forbearance condition in period 1 is satisfied if the value of delaying a payment and incurring initial forbearance costs plus further financing costs is less than the mortgage value when making the current payment, given the unemployment realization and the current-period individual expectations for α_i.

$$Forb_{i1} = V_{i1}^M - V_{i1}^F = mpay_1 - \frac{\alpha_{i1}(1+r)mpay_1}{1+r+b_i r^U} - C_i^F > 0 \tag{4}$$

For a sufficiently high cost of forbearance, the model predicts that forbearance options will rarely be executed, as was the case prior to March 2020. However, in late March 2020, forbearance costs were substantially reduced by the CARES Act. During this period, we assume that the forbearance option dominates the default option.[5]

Comparative statics of expected forbearance behavior from equation 4 are as follows.

$$\frac{\partial \Pr Forb_{i1} > 0}{\partial \alpha_{i1}} = -\frac{(1+r)mpay_1}{1+r+b_i r^U} < 0 \tag{5}$$

and

$$\frac{\partial \Pr Forb_{i1} > 0}{\partial b_i} = \frac{\alpha_{i1}(1+r)mpay_1 r^U}{(1+r+b_i r^U)^2} > 0 \tag{6}$$

An increase in house price expectations in period 1 leads to reduced forbearance because the probability of default in period 2 is reduced. In this case, the payment deferral becomes less valuable because principal and arrears are more likely to be paid. Evaluating the direction of change of individual expectations α_{1i} given a national expectations value α_1^N is a bit more complicated, and offers some interesting predictions. From equation 1, if $\alpha_1^N > \alpha_{i0}$, then a borrower who was pessimistic at origination would increase their expectations of future house price appreciation, leading to a lower forbearance probability. However, if $\alpha_1^N < \alpha_{i0}$ an optimistic borrower at origination would experience a reduction in future appreciation expectations, causing them to enter forbearance at higher rates.

Unemployment also increases the probability of forbearance. While this result is intuitive, the comparative statics from this simple model show that this is exclusively due to changes

[5] The expected value of the mortgage under the default option in period 1 is the same as the mortgage when making the payment. Default in period 1 is then chosen when $V_{i1}^H - V_{i1}^M + C_i^D < 0$, where $V_{i1}^H = rent_1 + \left(\alpha_{i1} P_2^G + (1-\alpha_{i1}) P_2^B\right) / (1+r+b_i r^U)$. See Foote et al. (2008b) for more discussion of the default option in a similar 2-period model.

in financing costs. If $r^U = 0$ and there is no additional cost to securing credit until period 2, then unemployment does not affect the forbearance probability. However, if the unemployed interest rate spread is high, forbearance is more likely. This comparative static for unemployment expectations has the same sign as that of observed unemployment.

2.3 Summary

Due to the perceived low costs of forbearance from the borrower's perspective, and the ease by which forbearance agreements were implemented, the number of loans in forbearance rose dramatically soon after the FHFA policy and the CARES act were implemented. According to the National Mortgage Database (NMDB), described in detail in the next section, the share of first-lien loans in the United States in forbearance rose from 0.3% in January, 2020 to 8.3% in May, 2020 (see Figure 1). Unlike the Great Recession, when the delinquency rate on home mortgages grew from 2% to 8%, the rate as reported by credit agencies declined from 3% to 1.8% early on in the pandemic (Cherry et al., 2021).[6] A primary reason behind the decline in the delinquency rate during the pandemic, rather than surge during the Great Recession, was the provision of forbearance.

The immediate questions then become which borrowers entered forbearance, exited forbearance with full repayment, and who remained in forbearance for extended periods? Specifically, what role did borrower expectations *at origination* play in forbearance uptake, and how did changing expectations affect forbearance behavior as the pandemic went on? As we show in the following sections, borrower and loan-level attributes that are typically used to explain defaults and prepayments (e.g. credit scores, DTI, LTV) are powerful predictors, in line with early-pandemic results found by McManus and Yannopoulos (2021) and others. But other variables on economic perceptions, financial sophistication, house price and job security expectations, and updates and outcomes to these expectations drove important differences in behavior. Much of these data are available in the National Mortgage Database and the associated National Survey of Mortgage Originations, which we will now describe.

[6]Broader definitions of delinquencies, such as in the Mortgage Bankers Association's (MBA) National Delinquency Survey, include both loans classified as delinquent by credit agencies and those in forbearance with borrowers not making payments. The MBA shows rates as high as 8% in 2020, similar to the NMDB forbearance measure.

3 Data and Measurement

3.1 Forbearance and Housing Expectations Data

In 2012, the Federal Housing Finance Agency (FHFA) and the Consumer Financial Protection Bureau (CFPB) began work on the National Mortgage Database (NMDB) and an associated new quarterly mail survey called the National Survey of Mortgage Originations (NSMO), which serves as our primary research dataset. A significant advantage of NSMO is that it surveys borrowers who have obtained a mortgage within the last six to nine months, meaning we capture the borrowers who are likely the most motivated and informed among the overall population. Their responses, especially concerning expectations, should be more informed than the general population because of their active participation in the market.

In 2021, the two agencies released the most recent public-use database covering 26 quarters of NSMO responses from mortgage originations in 2012 through 2019. While the public-use data top-codes or bins data and excludes all geographic and other identifying information, we draw on an expanded internal government database that relieves these constraints.[7] NSMO contains both survey responses and administrative data from NMDB obtained from a variety of sources including high-quality matches to administrative file records maintained by Fannie Mae, Freddie Mac, the Federal Housing Administration (FHA), the U.S. Department of Veterans Affairs (VA), the Rural Housing Service (RHS), and the Federal Home Loan Banks, which collectively account for over 70 percent of the mortgages in the U.S. NMDB and NSMO are augmented with other public and proprietary data sources, including deed record filings, HMDA filings, and commercially available servicing databases. Section A.1 of the Online Appendix provides selected variable definitions in our harmonized dataset.

The availability of high-quality administrative data for each sample loan from NMDB means that NSMO does not have to rely on the respondent to provide factual information about the mortgage itself. Thus, the survey instrument concentrates on obtaining information about the borrowers' knowledge, experience, perceptions, and expectations that are not readily captured anywhere else. The survey asks borrowers about their knowledge of mortgages prior to starting the process, their experience shopping for and closing on a mortgage, their perceptions of the housing market, and their future expectations about house price appreciation and critical household and financial events. The survey also contains demo-

[7] See Redmer (2019) for early evidence from NSMO relating expected and actual house price appreciation.

graphic, household composition, and other covariate information (e.g., risk preferences and financial sophistication metrics) that is not available in the NMDB. NSMO data matched to the NMDB contains variables drawn from both survey responses and from the NMDB administrative data file, including monthly mortgage performance after origination.

To address potential survey non-response bias, we use NSMO analysis weights for sampling rate variability that is associated with observables. Non-response bias results when survey respondents differ systematically from non-respondents and at the same time, responses vary. In practice, with a response rate of around one-third of sampled borrowers who completed the survey in each of the 26 waves, NSMO raw survey responses are not quite representative of the borrower population as a whole. Analytic weights assure a distribution among demographic and loan categories that is consistent with borrowers in NMDB. The specific sample of NSMO loans used in all forbearance analysis consists of all loans in the NMDB with a NSMO survey response that were current as of December 2019.

Table 1 documents the relative symmetry between NMDB and the weighted NSMO sample as well as several patterns about forbearance during the COVID-19 pandemic as captured by both NMDB and NSMO. 10.8% of all loans active in NMDB and 10.4% of all loans in the weighted NSMO sample entered forbearance at some point between January 2020 and March 2021. Similarly, 8.0% of loans in the NMDB entered forbearance at some point in 2020 versus 8.6% in the weighted NSMO sample.

3.2 Descriptive Statistics

Table 2 documents various geographic, loan-level, and borrower-level variables, both by forbearance status in 2020 and pooled together. We see that roughly 20% of the sample expected that housing prices would increase by "a lot," 59% that they would increase by "a little," and 18% that they would remain roughly the same. Only 3% believed that housing prices would decrease. But these expectations vary by forbearance status: those in forbearance are 5 percentage points more likely to expect house prices to increase a lot—an economically significant amount since it is a quarter of the average share. We also see differences in expected future unemployment (17% for those in forbearance while only 13% for those who did not take the option). Those in forbearance also live in areas with greater and more variable unemployment, are more likely to be self-employed, and have slightly lower household income. They are also less likely to be White, college-educated, and more likely to be borrowers of color. Those in forbearance also are much more likely to have a government-backed loan (38% versus 23%), have lower credit scores (712 versus 744), and are less likely to have a 3-month income reserve (65% versus 72%). In sum, these descriptive results are consistent with Gerardi et al. (2013) about negative selection into default.

Figure 2 examines the forbearance rate, coupled with the average among the set of borrowers who expect a layoff and those who expect house prices to appreciate "a lot" or "a little." While average national forbearance rates surged to 4%, they increased even more among both sets of borrowers expecting layoff and house price growth to roughly 6.1%. However, the two sets subsequently experienced vastly different dynamics. On one hand, forbearance rates among house price optimists began to decline and trend almost exactly as the national average. On the other hand, forbearance rates among those anticipating layoffs remained high at roughly 6% until mid 2021. These patterns match our theoretical predictions: house price optimists were initially worried at the onset of COVID-19, so they were more likely to enter forbearance, but after that uncertainty was resolved, they exited forbearance. In contrast, borrowers who anticipated losing their jobs were more likely to remain in forbearance and thus those still in forbearance by late 2021 were those who were unable to repay.[8]

To better understand the conditional link between expectations and forbearance, we draw on several data sources. Because expectations in NSMO are measured at loan origination, it is also useful to understand how these expectations for different cohorts of borrowers are associated with alternative expectations series and actual outcomes. Figure 3, panel (a) shows that each successive wave of NSMO respondents has expectations that evolve in a similar manner with the national Michigan Survey of Consumer Sentiment. Two things are noteworthy from this panel. First, NSMO respondents are much more optimistic in every period, with an average of about 80% of households expecting future appreciation, versus the Michigan Survey respondents, of which 50% expect future appreciation.[9] Second, both expectations series experienced major drops immediately following the initial lockdowns in March 2020. However, these expectations quickly recovered in the months that followed. Panel (b) shows house price appreciation and expectations of future growth are positively related. House price appreciation is measured with a substantial lag, so expectations may

[8]See Figure A.1 in Section A.1 of the Online Appendix for graphical evidence of spatial heterogeneity in expectations and forbearance rates across states.

[9]The horizon in the NSMO survey question is 2 years; the horizon in the Michigan Survey is 1 year. NSMO respondents have purchased or refinanced within the last 6-9 months, while Michigan respondents identify as either prospective buyers or homeowners for an unspecified period of time.

serve as a reasonable nowcast of appreciation. Panels (c) and (d) show that expectations of future individual layoffs in NSMO are associated with the current national labor market. Borrowers originating mortgages in periods with reduced national year-on-year income growth or higher unemployment rates are more likely to expect future layoffs for themselves.

Figure 4 shows how these series are associated with forbearance: those with optimistic house price expectations at origination in NSMO versus the Michigan Survey responses (a) and those with layoff expectations at origination in NSMO versus the Michigan Survey share of responses reporting income declines from a year ago (b). We find that the two series track each other closely in both panels: those who were appreciation optimists at origination went into forbearance at higher rates as national expectations fell and exited forbearance as the national mood improved. However, the layoff pessimists that entered forbearance at higher rates at the beginning of the COVID period remained in forbearance for longer, consistent with the notion that they did in fact become unemployed and remained so.

4 Estimating Effects of Expectations on Forbearance

4.1 Identification Strategy

Our model from Section 2.2 predicts that for a seasoned loan, execution of the forbearance option is a function of borrower-level house price expectations and labor market outcomes. Assuming an adaptive expectations process, house price expectations in the current period are based on both house price expectations at origination and updates to those expectations through changes in national perceptions. Labor market outcomes are correlated with individual labor market expectations formed at origination; those who expect to be laid off at some point in the future are assumed to, in fact, lose their jobs at higher rates.

Equation 7 models forbearance status $f = \{0, 1\}$ for individual i in month t using a linear probability model. In this equation, τ indexes the origination period of the loan, and t indexes the performance period in the COVID-19 forbearance era:

$$f_{it} = \boldsymbol{\zeta}_i + \boldsymbol{\lambda}_t + \gamma_h e^h_{i\tau} \times e^{hN}_t + \gamma_u e^u_{i\tau} \times u_{ct} + \epsilon_{it} \tag{7}$$

where $\boldsymbol{\zeta}$ is a vector of borrower-level fixed effects, $\boldsymbol{\lambda}$ is a vector of time-period fixed effects,

$e^h_{i\tau}$ and $e^u_{i\tau}$ are housing appreciation and future layoff expectations held by borrower i in origination period τ, e^{hN}_t are national housing expectations during the forbearance period, and u_{ct} is the unemployment rate in the borrower's county c in time t.

The interaction terms with coefficients γ represent interactions of initial expectations with updates to those expectations and economic outcomes. When the interaction of the two variables involves initial and contemporaneous expectations, the parameter has an adaptive expectations interpretation. For example, if initial expectations are pessimistic but current expectations are optimistic, then the interaction represents a positive change in expectations. Similarly, if initial and current expectations are matched, then the change is zero. For interactions involving initial expectations and an observed outcome, the interaction is interpreted as an individual-specific shock: if the outcome is in line with expectations, then the shock is zero; if the outcome is different, then the shock is positive or negative.[10]

Our identification strategy involves three key assumptions. First, our inclusion of borrower fixed effects purges unobserved heterogeneity between expectations and selection into forbearance, allowing us to trace out how a single borrower varies in probability of forbearance as the wedge between origination expectations and contemporaneous sentiment evolves over time. Even though we only observe borrower-specific house price and job loss expectations at the time of origination, we can see how groups with different expectations react to changes in national house price sentiment and labor market outcomes through the interaction term coefficients γ. Second, our inclusion of time fixed effects controls for the broad macroeconomic dynamics that were present in the housing and labor markets. Third, forbearance behavior during the pandemic is uncorrelated with loan survival into the beginning of the pandemic period, which we can (and do) empirically test and show holds in practice.

Our empirical specification makes a substantial refinement upon prior research that has only had access to cross-sectional variation: by including borrower fixed effects, we control for factors that are both unobserved and correlated with forbearance uptake during the pandemic. This is a notable improvement on models of mortgage performance that include

[10]To illustrate, suppose that at loan origination, borrower A expects house prices to appreciate "a lot" and borrower B expects prices for prices to "stay the same". Then, some period later, national sentiment has dropped relative to the origination period. The simple representation of adaptive expectations in Equation 1 suggests expectations will change more for borrower A than for borrower B, all else equal, because B's prior expectations were more in line with later-period sentiment than borrower A's.

static variables, including expectations measures (e.g. Cherry et al., 2021; McManus and Yannopoulos, 2021). In sum, the availability of borrower-level panel data allows us to exploit plausibly exogenous variation in the timing of borrowers who originated loans at different points in time and were, therefore, subject to different economic conditions as the loan evolved. Under our more relaxed assumptions, we can recover a plausibly causal effect of borrower expectations on mortgage performance, namely forbearance.

4.2 Main Results

Estimates from various models represented by Equation 7 are shown in Table 3. These models consider the effects of borrower-level expectations on execution of forbearance options for each month between January 2020 and January 2022, just before and during the COVID-19 pandemic. The coefficients of interest are γ_h and γ_u, the effects of changing house price expectations and unemployment shocks, respectively. The sample is the 24,575 loans with a NSMO survey response in the NMDB that are active in December 2019.

Column 1 presents our main results. Borrowers who were optimistic about house price appreciation when they purchased their home went into forbearance at higher rates when the national house price expectations climate turned negative in April 2022.[11] When expectations snapped back to being mostly positive in the months that followed, forbearance rates quickly fell. The negative-signed parameter on $e^h_{i\tau} \times e^{hN}_t$ shows that, among borrowers who expected price appreciation at origination, a drop in national price expectations leads to a sharper increase in forbearance uptake relative to those who expected no price appreciation.[12] The point estimate of -0.06 suggests that a 10 percentage point increase in the fraction of borrowers expecting negative appreciation increases forbearance rates by 0.6%. This share rose from 5% to 25% between January and April 2020, indicating a differential forbearance rate of 1.2% among borrowers who were optimistic about appreciation at origination.

This model also shows that borrowers who (at origination) expected a layoff were substantially more likely to enter forbearance as the labor market deteriorated. The point estimate on the interaction $e^u_{i\tau} \times u_{ct}$ of 0.15 implies that the increase in unemployment rate from 4% to 14% resulted in differential forbearance rates of 1.5% for households who expected a future layoff at the time of loan origination. Because the unemployment rate remained high, the

[11] The sample is reduced to 23,581 due to lack of degrees of freedom for some loans.

[12] The preferred measure of e^{hN}_t is $1 - s_t$, where s_t is the share of households in the Michigan Survey who expect house prices to fall over the next year. Other measures are shown to offer robust signs and magnitudes in the appendix.

forbearance rate for such borrowers also remained high for most of 2020, into 2021.

Column 2 replaces national price expectations with county appreciation to assess the role that actual experiences play vs those of expectations and shows a house price appreciation interaction of the same sign (negative) and significance. Column 3 includes both expectations and appreciation in the COVID-19 period interacted with expectations at origination with only small changes in point estimates, suggesting each is contributing useful, orthogonal information. Column 4 replaces actual county unemployment with national sentiment about decreasing household income and demonstrates that the differential effect among borrowers expecting unemployment is of the sign and significance as the county-level unemployment measure. Finally, column 5 includes all four variables with the national income measure dominated by the county-level unemployment, but all other estimates remain similar.

These estimates condition on borrower-level fixed effects and time period fixed effects. Thus, the parameters represent factors related to a borrower that are changing over time. The differentials estimated are smaller than those shown in Figure 2, where unconditionally, house price optimists had a 2pp higher forbearance rate in April 2020 versus the conditional differential of 1.2pp. Similarly, the unconditional differential for those expecting future layoffs was about 1.7pp versus the conditional differential of 1.5pp. Our causal estimates therefore capture over half of the unconditional differentials with the remaining unconditional differential attributed to differences in static effects across households and attenuation bias caused by imprecise measures.

4.3 Static Borrower-Level Attributes and Forbearance

The richness of the NSMO dataset allows us to investigate further the uptake of forbearance for borrowers of different types. For this set of models, we relax our borrower-specific fixed effects to include vectors of state and origination year fixed effects and both loan and borrower characteristics, including standard measures in mortgage databases (e.g., credit score, DTI, LTV, age, gender, education) and novel measures unique to NSMO (e.g., financial sophistication, risk preferences, beliefs regarding strategic default). To estimate these static effects, the dependent variable is now $f_{i2020} = \{0, 1\}$, which is set to 1 if the borrower executes the forbearance option in any month of 2020 and 0 otherwise, regardless of duration or dynamics.

$$f_{i2020} = \boldsymbol{\zeta}_s + \boldsymbol{\lambda}_\tau + \gamma_h e^h_{i\tau} + \gamma_u e^u_{i\tau} + \mathbf{D}'_{i\tau}\boldsymbol{\alpha} + \mathbf{X}'_{i\tau}\boldsymbol{\beta} + \epsilon_i \tag{8}$$

where $e^h_{i\tau}$ and $e^u_{i\tau}$ are expectations on future house price appreciation and job loss propensity formed in the origination period τ, $\mathbf{D}$ denotes a vector of loan-level characteristics, $\mathbf{X}$ denotes a vector of individual-level characteristics, and $\boldsymbol{\zeta}$ and $\boldsymbol{\lambda}$ denote fixed effects for each state and origination time period, respectively. These fixed effects allow us to isolate variation in expectations among observationally equivalent people in the same state over time, purging heterogeneity in state policies and aggregate risk over the COVID-19 period.

Here, our identifying variation comes from comparisons of borrowers who are indistinguishable based on observable demographic and loan characteristics within the same state and origination year, but differ in their underlying expectations about house prices and/or future employment status. We present estimates with and without loan-level characteristics to gauge their importance in explaining forbearance outcomes. Our primary concern is that we may fail to control for unobserved heterogeneity that jointly affects selection into the 2020 U.S. mortgage portfolio (vs prior prepayment or default), forbearance during the COVID-19 period, and initial borrower expectations.

While it is standard in studies on forbearance to control for demographic characteristics (McManus and Yannopoulos, 2021; Cherry et al., 2021; Fuster et al., 2021; An et al., 2021), to our knowledge, no one has yet to also incorporate loan-level information and other proxies for preferences and abilities, such as risk aversion and financial sophistication. These NSMO survey covariates are important in helping us to isolate more fully the causal effects of expectations on mortgage performance outcomes, which becomes clear as the controls are sequentially added. Nonetheless, we recognize the potential for remaining omitted variables, which is why this is not our primary specification.

4.4 Static Results

Table 4 documents our static results of forbearance uptake at any point in 2020, starting with a cross-sectional comparison in column 1. Here, we find that borrowers who believed that house prices would "increase a lot" and "increase a little" were 3.44pp and 0.98pp, respectively, more likely to enter forbearance, relative to those who anticipated "no change." Following our adaptive expectations interpretation from the longitudinal results, the reason house price optimistic borrowers are more likely to enter into forbearance is that expectations of future appreciation declined dramatically at the beginning of the pandemic. Reinforcing this idea is the ordering of the point estimates, with the most optimistic–even among optimists–facing higher rates of forbearance. We also see that those expecting unemployment are 2.23pp more likely to enter forbearance. As the labor market deteriorated, we presume those expecting to become unemployed in the future did in fact become unemployed.

While these estimates are consistent with theory, and are easily recognizable from our national time series in Figure 2, they could reflect unobserved heterogeneity: borrowers who enter forbearance are negatively selected, so differences in expectations could reflect other confounding attributes. Column 2 introduces year of origination and state fixed effects. Now the coefficients on “increase a little” and “decrease a little/lot” decline in economic and statistical significance, while the coefficient remains significant for those who are optimistic about house prices. Column 3 controls for local factors by introducing the change in the local unemployment rate and house price appreciation since 2019; the results are unaltered. Column 4 subsequently introduces a wide array of loan-level and borrower characteristics, ranging from their credit score to debt-to-income and loan-to-value ratios. Column 5 controls for borrower demographics, including, marital status, household income, age, gender, and race. Our results broadly remain similar, although now those who believe house prices would “increase a little” also have a 1.14pp higher probability of entering forbearance, compared with those who believe they would “increase a lot” with a 1.6pp probability.

Finally, column 6 controls for other factors that are typically unobserved in survey data. For example, we observe measures of borrowers’ financial knowledge and risk appetite, as well as self-employment status. Those with greater financial knowledge are less likely to enter forbearance. Importantly, our main results remain: those who are optimistic about house prices at origination are more likely to enter forbearance, as are those who expect future unemployment. The positive correlation is consistent with our model of forbearance under adaptive house price expectations, which predicts greater uptake among those borrowers who had the highest expectations of future house prices at origination and, thus, experienced the largest decrease in expectations when national expectations trended downward in mid-2020. We find no statistically significant differences in forbearance uptake among borrowers who expected house prices to “decrease by a little/a lot” at origination as these borrowers likely experienced less of a decline in individual expectations when national expectations soured.

4.5 Extensions: Heterogeneity

Das et al. (2020) emphasize that there is substantial heterogeneity across different socio-economic brackets. While our dynamic specification exploits within-borrower variation, and our cross-sectional regressions contain detailed borrower characteristics, Table 5 allows for heterogeneous treatment effects across several partitions of the data: race, first-time home buyers, and credit score. The relationship between house price (and job loss) expectations and forbearance is strongest for borrowers self-identifying as white/non-Hispanic, first-time home-buyers, and those with a credit score below 690. These results are consistent with what we would expect, particularly expectations at origination for first-time home buyers being a more significant anchor than for those who have been through the process before.

Table 6 presents analogous results where we interact each categorical response on expectations with loan and demographic characteristics. Of note, there is a positive non-linear relationship between expectations and forbearance for increases in the loan amount and monthly mortgage payment, consistent with our forbearance model.

4.6 Robustness: Selection Effects

One potential concern with our main result is that our linear probability model fails to properly account for selection effects during the unique COVID-19 era: if selection into our sample is both correlated with forbearance and our expectations measures, our estimates will be biased. While there is no way to fully account for selection effects, we can exploit our detailed borrower characteristics to gauge the degree to which different assumptions about the residual or observed characteristics influence our estimates.

Table 7 replicates our main static results linking forbearance with house price and unemployment expectations at origination. Columns 1 and 2 present the marginal effects with a linear probability and probit model, respectively, demonstrating that both models produce similar average treatment effects. Column 3 uses a Heckman-style probit model (Van de Ven and Van Praag, 1981) where the selection equation is function of interest rates at origination interacted with the year of origination. The identifying assumption is that decisions made years in advance are uncorrelated with plausibly exogenous changes in interest rates in the COVID-19 era, but nonetheless affect the probability of forbearance through their effects on borrower expectations. (Consistent with this assumption, Table 4 shows no effect of the interest rate spread on forbearance outcomes during the COVID-19 period.)

Column 3 includes no controls other than specifying and identifying the selection equation, suggesting a high correlation between selection and probit equation residuals, $\rho = -0.175$, indicating selection bias in columns 1 and 2, and a small p-value for a Wald test of equivalence between models with and without selection of 0.001. As controls are added in columns 4 through 6, the residual correlations and Wald test p-values decline to statistical insignificance. Comparing the marginal effects of columns 6 through 8 assesses the role of selection and estimators in estimation of marginal effects with a full set of borrower, demographic, and fixed-effect controls. These models show expectations parameters that are all generally similar, suggesting the original results in Table 4 gives reasonable estimates of causal average treatment effects. While there is strong evidence of a non-random selection process, this process does not appear to influence the estimates due to the richness of our control set. Expectations drive both selection into the sample and loan performance in the COVID-19 period, but our control set adequately controls for bias-inducing selection effects.

5 Determinants of Expectations at Origination

5.1 Identification Strategy

While we have shown how expectations at origination influence forbearance, what explains how borrowers form these expectations? In addition to decomposing expectations into loan characteristics and borrower demographics, as well as local conditions, we also explore how network house price appreciation and the network unemployment rate are related with expectations at origination. Our network measure reflects the exposure of borrowers within a given county to the local conditions in other counties as a function of their friendship ties through Facebook, which we explain further. We estimate the following models:

$$e^k_{ic\tau} = \boldsymbol{\zeta}_s + \boldsymbol{\lambda}_\tau + \xi_h \Delta h^d_{c\tau} + \xi_u u^d_{c\tau} + \psi_h \Delta h^{SCI}_{c\tau} + \psi_u u^{SCI}_{c\tau} + \mathbf{D}'_{i\tau}\boldsymbol{\alpha} + \mathbf{X}'_{i\tau}\boldsymbol{\beta} + \epsilon_{i\tau} \tag{9}$$

where $e^k_{ic\tau}$ denotes individual i's expectations about variable $k = \{h, u\}$ (house prices or job loss, respectively) in state s with origination period τ, $\Delta h^d_{c\tau}$ denotes year-on-year house price growth, $u^d_{c\tau}$ denotes the unemployment rate, $\Delta h^{SCI}_{c\tau}$ denotes an average house price growth rate for households in the borrower county c's average social network (SCI), and $u^{SCI}_{c\tau}$ denotes SCI-weighted unemployment. Standard errors are clustered at the state-level to allow for correlation of errors in the same area over time.

There are two main identifying assumptions necessary to interpret the ξ parameters in Equation 9 as causal effects. First, we make a "small borrower" assumption, where an individual borrower cannot influence the house price appreciation nor the unemployment rate of the county. Second, we make a sorting assumption, where we require that the process by which a prospective homeowner chooses to live in a county or buy a house is independent of expectations, conditional on observables. Because optimistic borrowers are more likely to outbid non-optimistic borrowers for housing, this is likely to cause upward bias in parameters.

We address selection through a granular set of demographic and loan-level controls. In addition to standard demographics (e.g., age, race, marital status, education), we have a host of variables that are fairly unique to NSMO. We control for financial knowledge and risk tolerance, which reflect preferences in investment and overall financial sophistication. We control for household income, self-employment status, and a measure of present liquidity, which reflect internal resources and savings behavior. While none of these borrower-level controls are perfect by themselves, we show that our estimated coefficients are highly invariant to their inclusion, suggesting that selection effects are unlikely a major threat.

Finally, we control for state fixed effects to purge differences in expectations that might also be correlated with time-invariant characteristics of states, such as amenities, policies, and broad economic prospects. We also control loan origination year fixed effects to account for national factors at loan origination that may influence the general tenor of housing and labor market perceptions and heterogeneity in state and national policies.

5.2 Social Network Statistics

In models establishing determinants of expectations, we assess the role social networks play in forming these beliefs. Following the methods of Bailey et al. (2018), we use an extraction of 2019 Facebook data to construct a matrix of friendship ties between each county c and every other county c'. Friendship on Facebook is admittedly a crude proxy for relationship, but it has been a reliable approach to understanding the dissemination of information (e.g. Makridis, 2022). Using these friendship ties, we create a Social Connectedness Index (SCI) for any variable y measured at the county level as a weighted average of other county's values, where weights sum to unity:

$$y_{c,t}^{SCI} = \sum_{c' \neq c} (y_{c',t} \times SCI_{c,c'}/SCI_c) \tag{10}$$

where $SCI_{c,c'}/SCI_c$ denotes the relative share of county c' ties in county c. We exclude the friendship ties between a county and itself to omit any mechanical effects that could emerge.

We calculate SCIs for both house price appreciation and unemployment rates to assess the role social networks play in forming beliefs regarding expected house price appreciation and unemployment. House price indices are annual, county-level repeat-sales indices from Bogin et al. (2019) updated through 2021. These indices have an advantage over other sources of data on housing prices because they have excellent coverage and are constructed using repeat-sales, rather than estimated quantities. Unemployment rates are from the Bureau of Labor Statistics' Local Area Unemployment Statistics dataset.

5.3 Results

Table 8 documents our main results when house price expectations are the outcome variable. The house price expectations variable is ordinal, ranging from 0 ("down a little" or "down a lot") to 3 ("up a lot"), so coefficient estimates give advancement to the next category. Starting in column 1, we see that a 1pp rise in the SCI-weighted network appreciation of house prices is associated with a 0.040 increase in our measure of house price expectations, whereas the link for realized house price appreciation at origination is two-thirds that magnitude at 0.026. If "network" appreciation was 10% and own-county appreciation is 20%, then the predicted survey response would be 0.92 higher, or almost a full survey response category. Column 2 adds the SCI-weighted unemployment rate and the realized unemployment rate at origination, showing that the network variables are not simply capturing local heterogeneity.

However, these coefficients could be biased due to omitted variables, so we add origination year and state fixed effects as controls in column 3. The magnitude of SCI-weighted house price appreciation declines by nearly one-third in magnitude and approximately in line with the impact of realized house prices. Furthermore, the coefficient on SCI-weighted unemployment becomes negative, albeit statistically insignificant, and the coefficient on the unemployment rate remains negative and significant. Column 4 adds borrower demographic controls, strengthening the precision of our results and increasing the magnitude and significance of our SCI-weighted unemployment rate by purging selection effects that could have been generating bias. Higher income, male, college educated, and most borrowers of color are more likely to hold greater house price expectations at origination.

We may still fail to capture omitted variables, so we add our more granular controls for financial sophistication, risk appetite, self-employment, and the three month income reserve in column 5. Again, our results are not altered. Finally, to show that our smaller forbearance sample produces a similar pattern as our NSMO sample, column 6 only includes loans in the NMDB with a NSMO survey response that were current as of December 2019. Here, we see that a 1pp rise in house price growth and its SCI-weighted equivalent are associated with a 0.025 and 0.023 increase in predicted category of house price expectations, respectively, and a 1pp rise in the unemployment rate and its SCI-weighted equivalent is associated with a 0.015 and 0.024 decrease, respectively, in predicted category of house price expectations. These results suggest that the marginal effects are externally valid: they are not driven by variation unique to the COVID-19 pandemic. Furthermore, Table A.2 in the appendix replicates these results with an alternative model, i.e. an ordered logit.

We learn several lessons from these results on house price expectations. First, SCI-weighted house price appreciation and realized house price growth have associations that are similar in magnitude on house price expectation formation. Second, SCI-weighted unemployment rate has a greater effect than the actual local unemployment rate in developing house price expectations. These results are consistent with models where information diffuses more rapidly and pervasively through social networks, rather than just local information.[13] Third, SCI-weighted unemployment rate matters slightly more than the SCI-weighted house price appreciation for explaining house price expectations at origination after controlling for borrower attributes, but not before. That tells us that there are important selection effects with the diffusion of information that we control for through the inclusion of variables such as household income, education level, and race/ethnicity. Finally, our results are robust to the inclusion of typically unobserved borrower attributes, such as measures of financial sophistication and risk aversion, which gives us confidence that our estimates are not systematically biased by unobserved heterogeneity. Furthermore, both financial sophistication and risk appetite are strongly correlated with house price expectations at origination.

Table 9 explores analogous results when our outcome is unemployment expectations at orig-

[13] See Bailey et al. (2018) and Makridis (2022) for evidence in the context of the housing market.

ination. We do not find statistically significant results linking expected job loss with SCI-weighted unemployment rate or the network or local house price growth rate after controlling for state and origination year fixed effects. While the full NSMO sample shows that local unemployment has a small negative correlation with unemployment expectations, column 6 shows that the relationship becomes less statistically significant in the smaller forbearance sample of loans. Accordingly, while expectations common among individuals at a county level are useful for explaining house price expectations, borrower-specific observables and unobservables drive most of the variation in expectations of future job losses.

6 Expectations with Leverage and Debt Burden

Our results point towards the important role that expectations at the time of origination play in shaping forbearance outcomes. Prior research suggests expectations also play a role in determining a borrower's choice of loan terms (Brueckner, 2000; Bailey et al., 2019, e.g.). In present research, we cannot claim a causal relation between expectations and mortgage characteristics because we cannot rule out endogenous sorting. However, we can assess the degree to which expectations are associated with loan attributes at loan origination.

Table 10 presents models where we regress the loan-to-value (LTV) ratio and debt-to-income (DTI) ratio on borrower expectations, loan characteristics, and demographics. Starting with columns 1 and 4, which present expectations alone without controls, we find a strong positive association between those who believe house prices will "increase a lot" and both LTV and DTI. However, such a correlation could be heavily biased by omitted variables, so columns 2 and 5 introduce our baseline borrower controls. Indeed, we find that the correlation becomes statistically insignificant, although remaining economically significant, when LTV is the outcome variable, but those who believe that house prices will "increase a little" are now positively associated with LTV and DTI. These results are also robust when we restrict the sample to the matched NMDB and NSMO samples: increases in house price expectations are positively associated with DTI and, at least for the partial house price optimists, LTV. Overall, we estimate a categorical increase in the house price expectations to increase LTVs by about 1pp and DTIs by about 1.5pps, conditional on controls.

The robust association between expectations and both LTV and DTI even after controlling for borrower characteristics and origination year and state fixed effects tells us that expectations shape the amount of leverage and debt burden that borrowers take on through the loans that they originate. Our theoretical model predicts that optimistic borrowers are more likely to enter forbearance when their expectations about home values and household income begin to sour. These selection effects are especially concerning if these optimistic expectations led them to take further leverage and debt than they otherwise would at origination. In this sense, our results have implications for policy: changes in the real economy may not necessarily prompt borrowers (and the composition) into action if they have strong priors from their origination expectations (Piskorski and Seru, 2018).

7 Conclusion

There is now a large body of empirical literature pointing towards the importance of expectations on aggregate activity (Malmendier and Nagel, 2011; Bailey et al., 2018; Gillitzer and Prasad, 2018; Makridis, 2022), as well as quantitative macroeconomic models that embed expectations in a realistic and tractable way (Kaplan et al., 2020). These studies highlight the importance of local and/or demographic factors in shaping beliefs about house prices and the national state of the economy (Adelino et al., 2018; Das et al., 2020).

However, much less research has provided a unified theory linking expectations, loan origination, and, crucially, loan performance. Using comprehensive and detailed longitudinal data, coupled with the substantial variation in loan performance and interest rates observed since 2019, we quantify the effect of borrower house price expectations on the probability of entering forbearance. We find that borrowers who are optimistic about house prices are more likely to enter forbearance as national expectations sour, consistent with our stylized theoretical model that embeds house price and job loss expectations. We subsequently decompose the determinants of house price expectations and show that shocks to a borrower's social network at the time of origination have substantial effects on their beliefs, consistent with past empirical work. Finally, we show that more optimistic house price expectations at the time of origination drive up leverage and debt burden.

Our results have important implications for ongoing policy debates about the role of macroprudential policy (Piskorski and Seru, 2018). In particular, expectations—both at the time of loan origination and changes in the national climate—are an important driver of loan performance, but it is an avenue that has received limited to no attention. It remains to be seen whether those effects outweigh the impact of policy nudges or interventions (i.e., since that implies a role of selection effects in driving borrowers to certain loans over others).

Nonetheless, our research opens many new questions for further research.

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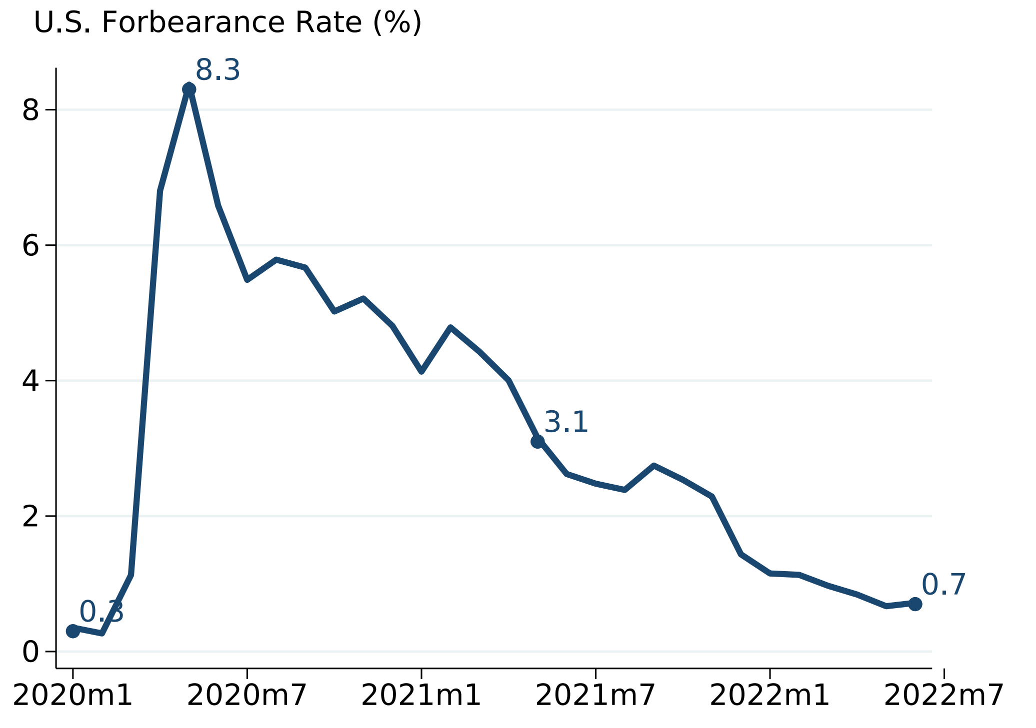
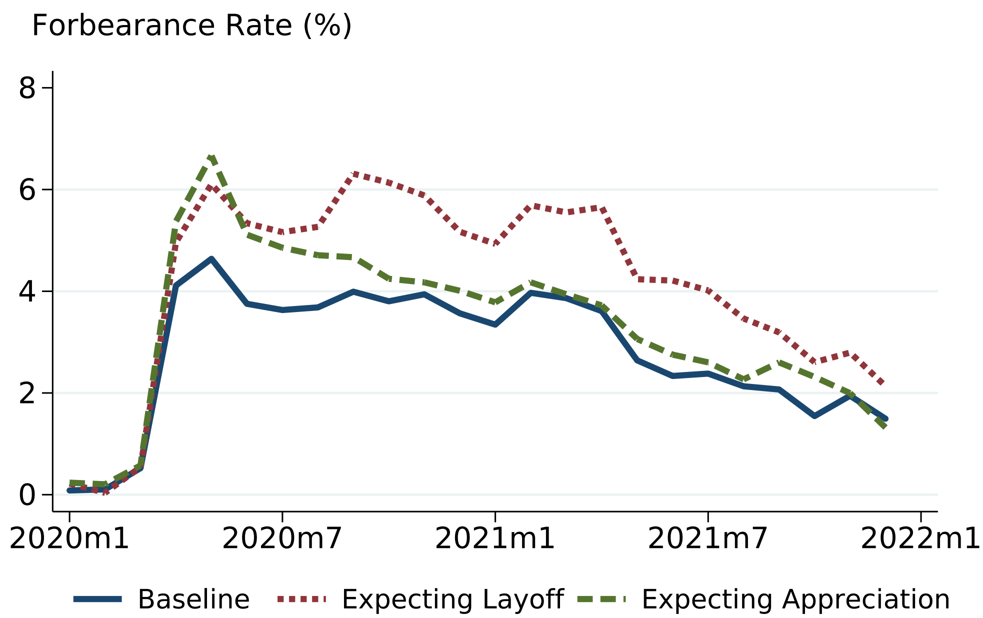
Figure 1: Share of Active Loans in Forbearance



Source: National Mortgage Database.

Notes: The figure plots the share of active loans that were in forbearance as of the particular month.

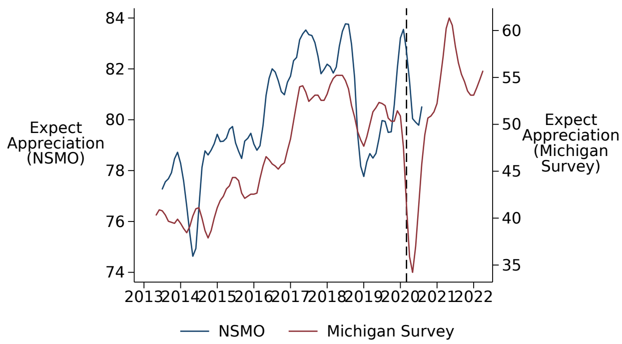
Figure 2: Time Series of Forbearance by Prior Beliefs (At Loan Origination)



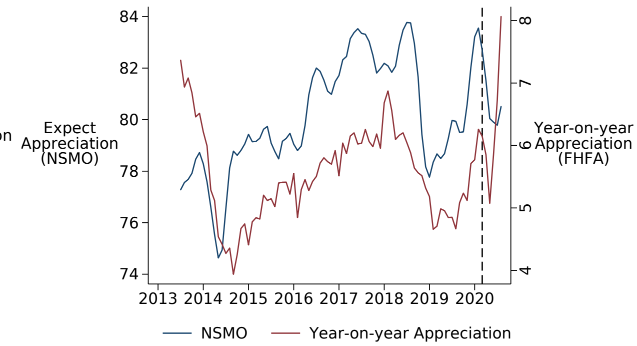
Sources: National Mortgage Database and National Survey of Mortgage Originations.
Notes: The figure plots average forbearance rates (weighted) based on beliefs held at loan origination. The sample is all loans in the NSMO sample that were active and current as of December, 2019 and still active as of the particular month. *Forbearance* is set equal to one if the loan is in forbearance in the particular month or zero if it is active and not in forbearance. *Expecting Appreciation* is defined at origination based on question 69 in the NSMO survey, *What do you think will happen to the prices of homes in this neighborhood over the next couple of years* set to one if the response is *Increase a lot* or *Increase a little*. *Expecting Layoff* is defined based on question 95c in the survey, *How likely is it in the next couple of years that you or your spouse will face...a layoff, unemployment, or a forced reduction in hours*, with *somewhat likely* or *very likely* set to one and zero otherwise.

Figure 3: Expectations and Outcomes

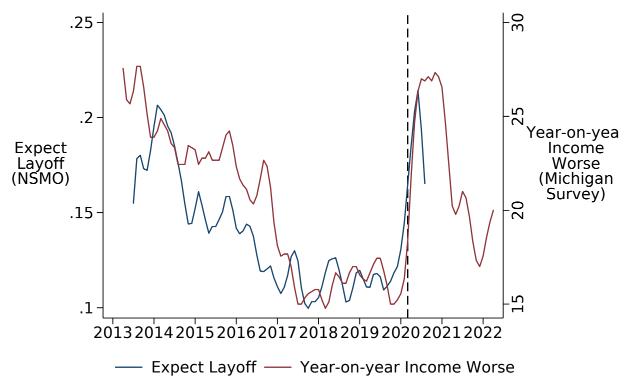
(a) House Price Expectations, NSMO vs Michigan Survey



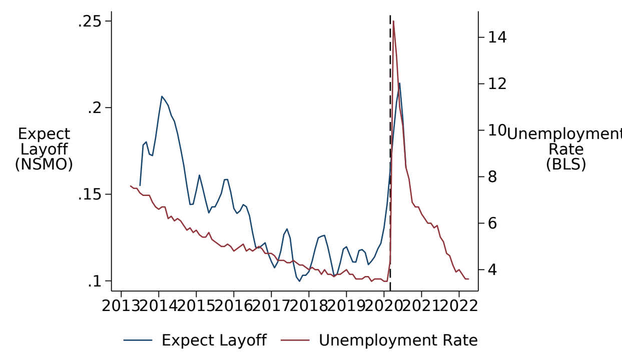
(b) House Prices, Expectations vs Actuals



(c) Layoff Expectations vs Lagged Incomes



(d) Layoff Expectations vs Unemployment Rate

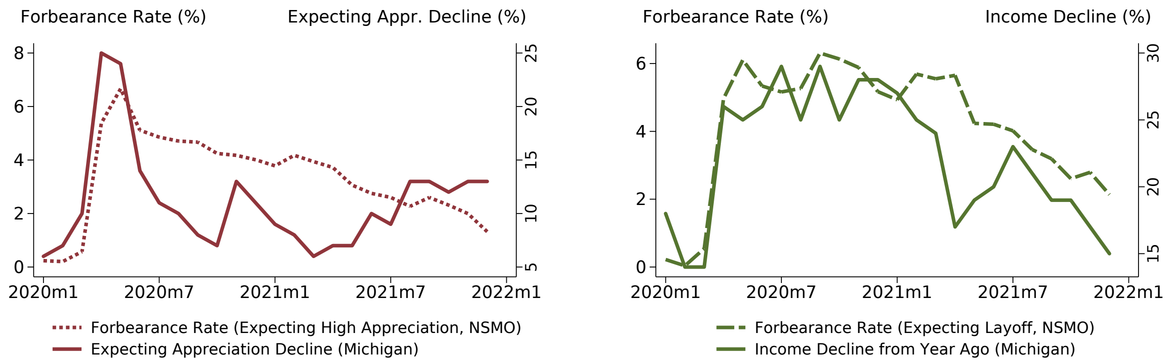


Sources: National Mortgage Database's National Survey of Mortgage Originations (a-d), Michigan Survey of Consumers (b,c), Federal Housing Finance Agency (b), and Bureau of Labor Statistics (d).

Notes: The figures present shares of loans in the NMDB with a NSMO survey response alongside other measures. The NSMO survey responses are lagged six months and smoothed based on a moving average process to account for variation in survey timing. Panel (a) shows the share of borrowers who were optimistic views regarding future appreciation at loan origination, versus real-time estimates of the share of respondents from the Michigan Survey who expected house price appreciation. Panel (b) shows NSMO optimists versus the U.S. average appreciation rate. Panel (c) shows the share of borrowers who expected a future layoff at loan origination, versus the share of respondents in the Michigan Survey who experienced a deteriorating income situation over the last calendar year. Panel (d) shows future layoff expectations versus the U.S. unemployment rate.

Figure 4: Forbearance Rates by Updated and Resolved Expectations

(a) Updated Expected Appreciation (b) Resolved Income Changes



Sources: National Mortgage Database, National Survey of Mortgage Originations, and Michigan Survey of Consumers.

Notes: The figures present shares of loans in the NMDB with a NSMO survey response that were current in December 2019, and still active as of the particular month. Panel (a) shows the subset of borrowers who were held optimistic views regarding future appreciation at loan origination, versus real-time estimates of the share of respondents from the Michigan Survey who expected house price appreciation declines. Panel (b) shows the subset of borrowers who expected a future layoff at loan origination, versus the share of respondents in the Michigan Survey who experienced a deteriorating income situation over the last calendar year.

Table 1: Forbearance Statistics through July 2022

	Count	% of Total
Total NMDB, Active Jan. 2020 through July 2022	3,522,848	
Never in forbearance	2,861,501	81.2%
Ever in forbearance	379,900	10.8%
Ever in forbearance in 2020	283,348	8.0%
Total NSMO Sample, 2013-2020 originations	40,039	
Total NSMO Sample, Current Dec. 2019 (unweighted)	24,575	
Never in forbearance (unweighted)	22,295	90.7%
Ever in forbearance (unweighted)	2,280	9.3%
Ever in forbearance in 2020 (unweighted)	1,849	7.5%
Never in forbearance (weighted)	22,470	91.4%
Ever in forbearance (weighted)	2,564	10.4%
Ever in forbearance in 2020 (weighted)	2,105	8.6%

Sources: National Mortgage Database and National Survey of Mortgage Originations.

Notes: The total count for the NMDB includes all loans active at any point between January 2020 and July 2022. The NSMO sample of loans consists of all loans in the NMDB with a NSMO survey response that were current in December 2019. The NSMO sample is weighted to account for non-response bias and sampling rate variability and then normalized such that the average analytic weight for loans that survived to Dec. 2019 equals 1.

Table 2: Descriptive Statistics by Forbearance Status

	All Current in Dec. 2019		In Forbearance in 2020		Not in Forb. in 2020	
	Mean	SD	Mean	SD	Mean	SD
Origination Appreciation Expectations						
Increase a lot	0.20	0.40	0.25	0.43	0.20	0.40
Increase a little	0.59	0.49	0.57	0.50	0.59	0.49
About the same	0.18	0.38	0.15	0.36	0.18	0.38
Decrease a little/lot	0.03	0.16	0.03	0.16	0.03	0.16
Expect future Unemployment	0.14	0.34	0.17	0.37	0.13	0.34
Appreciation at Origination	5.13	3.50	5.46	3.58	5.10	3.50
Appreciation, Origination-2019	19.31	14.20	18.90	14.13	19.35	14.21
Appreciation, 2019-2020	3.50	1.91	3.38	1.81	3.51	1.91
Network Appreciation at Origination	3.74	1.40	3.96	1.27	3.72	1.41
Unemployment Rate at Origination	5.03	1.82	5.04	1.86	5.02	1.81
Change in U. Rate, 2019-2020	7.08	3.03	7.82	3.30	7.01	3.00
Change in U. Rate, 2020-2021	-5.02	2.19	-5.39	2.31	-4.98	2.17
Network Unemployment Rate	5.31	1.39	5.25	1.27	5.32	1.40
Credit Score	741	64	712	67	744	63
Debt-to-Income ratio	36	12	40	12	36	12
Loan-to-Value ratio	78	20	81	18	77	20
Purchase	0.55	0.50	0.60	0.49	0.54	0.50
Rate/Term Refinance	0.27	0.44	0.23	0.42	0.27	0.44
Cash-out Refinance	0.17	0.38	0.16	0.36	0.17	0.38
Private Backed	0.16	0.37	0.09	0.29	0.17	0.37
Government Backed (vs Private)	0.24	0.43	0.38	0.49	0.23	0.42
Enterprise Backed (vs Private)	0.60	0.49	0.53	0.50	0.61	0.49
National Int Rate at Origination	3.84	0.48	3.92	0.43	3.83	0.48
Rate Spread at Origination	0.22	0.72	0.26	0.57	0.22	0.73
First-time home buyer	0.26	0.44	0.35	0.48	0.25	0.43
Household Income	102,450	82,719	96,484	78,449	103,009	83,088
Male	0.56	0.50	0.53	0.50	0.56	0.50
Married	0.66	0.47	0.66	0.47	0.66	0.47
Age	46.32	13.76	43.80	12.61	46.55	13.84
College Graduate	0.64	0.48	0.57	0.50	0.65	0.48
White, non Hispanic	0.74	0.44	0.60	0.49	0.75	0.43
Hispanic (any)	0.13	0.33	0.20	0.40	0.12	0.33
Asian	0.06	0.23	0.08	0.27	0.06	0.23
Black	0.06	0.24	0.11	0.31	0.06	0.23
Other race/ethnicity	0.02	0.15	0.03	0.17	0.02	0.15
Financial Knowledge	0.69	0.22	0.64	0.23	0.69	0.22
Risk Appetite	0.34	0.27	0.33	0.29	0.35	0.27
Employed Member of Household	0.50	0.50	0.52	0.50	0.50	0.50
Self-Employed	0.10	0.30	0.15	0.35	0.09	0.29
3 Month Income Reserve	0.71	0.36	0.65	0.38	0.72	0.36
Observations	24,575		2,105		22,470	

Sources: National Mortgage Database and National Survey of Mortgage Originations for mortgage and survey data. House price data are from Bogin et al. (2019). Unemployment rates are from Bureau of Labor Statistics' Local Area Unemployment Statistics database and are measured from April-April each year. Network variables are constructed off of the 2019 extraction of the Social Connectedness Index (SCI) where we take $y^{SCI} = \sum_{c' \neq c}(y_{c'} \times SCI_{c,c'}/SCI_c)$ where c denotes the county, $SCI_{c,c}$ denotes the number of friendship ties between county c and c', and $y_{c'}$ denotes either house price growth or the unemployment rate.

Notes: The baseline sample of loans consists of all loans in the NMDB with a NSMO survey response that were current in December, 2019. Reported statistics are based on survey weighted response values.

Table 3: Forbearance Rates by Updated and Resolved Expectations

	Dependent Variable: Forbearance in month t				
Model	[1]	[2]	[3]	[4]	[5]
Estimator	OLS	OLS	OLS	OLS	OLS
Estimate	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$
$e^h_{i\tau} \times e^{hN}_t$	-0.0618^{***}		-0.0537^{***}	-0.0513^{***}	-0.0534^{***}
	[0.0175]		[0.0170]	[0.0169]	[0.0170]
$e^h_{i\tau} \times \Delta p_{ct}$		-0.0725^{***}	-0.0672^{***}	-0.0668^{***}	-0.0674^{***}
		[0.0183]	[0.0179]	[0.0179]	[0.0179]
$e^u_{i\tau} \times u_{ct}$	0.154^{***}	0.153^{***}	0.157^{***}		0.122^{**}
	[0.0505]	[0.0504]	[0.0504]		[0.0527]
$e^u_{i\tau} \times \Delta income^N_t$				0.0872^{***}	0.0423
				[0.0303]	[0.0304]
Borrower FE	Yes	Yes	Yes	Yes	Yes
Time period FE	Yes	Yes	Yes	Yes	Yes
Observations	390,762	390,762	390,762	390,762	390,762
R-squared	0.002	0.019	0.021	0.049	0.054
Clusters	23,581	23,581	23,581	23,581	23,581

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Standard errors, clustered by borrower, in brackets. The dependent variable is forbearance status as of month t. This is estimated as a function of individual and time period fixed effects, and NSMO survey responses at origination interacted with COVID-era beliefs and economic outcomes. The model is estimated over monthly data from January 2020 through January 2022.

Definitions: $e^h_{i\tau}$, NSMO house price expectations at origination either "up a lot" or "up a little" in the "next couple of years"; $e^{hN}_t = 1 - s_t$, where s_t is the fraction of households responding to question 46 of the Michigan Survey of Consumers as "decline" in the next 12 months; Δp_{ct}, the year-on-year log-difference in the county home value index from Zillow; u_{ct}, the county-level unemployment rate from the Bureau of Labor Statistics; $\Delta income^N_t$, the fraction of households responding to question 7 of the Michigan Survey as "income as lower" than a year ago.

Table 4: Static Effects of Expectations on Forbearance in 2020

Dependent Variable: Entered Forbearance in 2020

Model	[1]	[2]	[3]	[4]	[5]	[6]
Estimator	OLS	OLS	OLS	OLS	OLS	OLS
Estimate	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$
Origination Appreciation Expectations						
Increase a lot	0.0344***	0.0205***	0.0193**	0.0166**	0.0160**	0.0173**
Increase a little	0.0098*	0.0040	0.0037	0.0098*	0.0114**	0.0120**
Decrease a little/lot	0.0126	0.0097	0.0080	0.0068	0.0056	0.0052
Expect future Unemployment	0.0223***	0.0237***	0.0230***	0.0213***	0.0207***	0.0202***
Appreciation, Origination-2019			−0.0005*	−0.0004	−0.0004	−0.0004
Change in U. Rate, 2019-2020			0.0059***	0.0060***	0.0052***	0.0052***
Credit Score				−0.0005***	−0.0004***	−0.0004***
Debt-to-Income ratio				0.0010***	0.0011***	0.0010***
Loan-to-Value ratio				0.0001	−0.0001	−0.0001
Enterprise Backed (vs Private)				0.0279***	0.0295***	0.0307***
Government Backed (vs Private)				0.0567***	0.0561***	0.0581***
National Int Rate at Origination				0.0102*	0.0118**	0.0111**
Rate Spread at Origination				0.0027	0.0031	0.0023
First-time home buyer				0.0136**	0.0098	0.0072
Rate/Term Refinance				−0.0068	−0.0071	−0.0075
Cash-out Refinance				−0.0090	−0.0077	−0.0077
Household Income (ln)					0.0097**	0.0089*
Male					−0.0088**	−0.0094**
Married					0.0128***	0.0133**
Age					−0.0007***	−0.0007***
College Graduate					−0.0199***	−0.0184***
Hispanic (any)					0.0125	0.0127
Asian					0.0296***	0.0291***
Black					0.0554***	0.0567***
Other race/ethnicity					0.0137	0.0139
Financial Knowledge						−0.0297**
Risk Appetite						0.0091
Employed Member of Household						−0.0025
Self-Employed						0.0497***
3 Month Income Reserve						−0.0054
Constant	0.0695***	0.0104	−0.0083	0.2195***	0.1362**	0.1495**
Origination Year DVs	No	Yes	Yes	Yes	Yes	Yes
State DVs	No	Yes	Yes	Yes	Yes	Yes
Observations	24,575	24,575	24,575	24,575	24,575	24,575
R-squared	0.002	0.019	0.021	0.049	0.054	0.057

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Robust standard errors omitted from table for brevity, but available upon request. The dependent variable is set to 1 if the loan entered forbearance at any point in 2020, and 0 otherwise. The sample in all models is all loans in the NMDB with a NSMO survey response that were current in December, 2019. Observation weights are normalized within each of these raw samples.

Table 5: Static Effects of Expectations on Forbearance in 2020, Sub-Samples

	Dependent Variable: Entered Forbearance in 2020						
	Static Col 6	White/non-Hisp	Minority	FTHB	non-FTHB	Credscore<690	Credscore≥ 690
Model	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Estimate	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$
Origination Appreciation Expectations							
Increase a lot	0.0173**	0.0239***	−0.0004	0.0405**	0.0100	0.0353*	0.0099
Increase a little	0.0120**	0.0161***	−0.0035	0.0223*	0.0070	0.0152	0.0094*
Decrease a little/lot	0.0052	0.0293*	−0.0602**	−0.0155	0.0152	−0.0449	0.0209
Expect future Unemployment	0.0202***	0.0176***	0.0232	0.0085	0.0245***	0.0318	0.0170***
Change in U. Rate, 2019-2020	0.0052***	0.0047***	0.0054**	0.0081***	0.0045***	0.0047	0.0053***
Appreciation, Origination-2019	−0.0004	−0.0003	−0.0006	−0.0010	−0.0002	−0.0015*	−0.0002
Household Income (ln)	0.0089*	0.0091**	0.0082	0.0160	0.0043	0.0152	0.0056
Male	−0.0094**	−0.0090*	−0.0083	−0.0318***	0.0001	−0.0157	−0.0064
Married	0.0133**	0.0075	0.0276**	0.0173	0.0116**	0.0157	0.0114**
Age	−0.0007***	−0.0005***	−0.0013***	−0.0000	−0.0009***	−0.0012**	−0.0006***
College Graduate	−0.0184***	−0.0141***	−0.0294**	−0.0051	−0.0208***	−0.0115	−0.0197***
Hispanic (any)	0.0127		0.0095	0.0290*	0.0032	0.0465**	−0.0028
Asian	0.0291***		0.0400	0.0395*	0.0256**	0.0371	0.0278***
Black	0.0567***		0.0570	0.0935***	0.0352***	0.0772***	0.0414***
Other race/ethnicity	0.0139		0.0165	0.0528	−0.0078	−0.0049	0.0227
Credit Score	−0.0004***	−0.0003***	−0.0006***	−0.0006***	−0.0004***	−0.0003	−0.0004***
Debt-to-Income ratio	0.0010***	0.0010***	0.0012***	0.0029***	0.0006***	0.0017***	0.0009***
Loan-to-Value ratio	−0.0001	−0.0000	−0.0003	−0.0000	−0.0000	−0.0000	−0.0001
Enterprise Backed (vs Private)	0.0307***	0.0251***	0.0505***	0.0255*	0.0315***	0.0576***	0.0261***
Government Backed (vs Private)	0.0581***	0.0490***	0.0815***	0.0745***	0.0397***	0.0870***	0.0424***
National Int Rate at Origination	0.0111**	−0.0008	0.0481***	0.0146	0.0132**	0.0395**	0.0063
Rate Spread at Origination	0.0023	0.0019	0.0017	−0.0004	0.0022	−0.0007	0.0031
First-time home buyer	0.0072	0.0001	0.0183			0.0485**	−0.0074
Rate/Term Refinance	−0.0075	−0.0042	−0.0141	0.0132	−0.0084	0.0052	−0.0105**
Cash-out Refinance	−0.0077	−0.0113*	0.0075	0.0353	−0.0071	0.0098	−0.0098*
Financial Knowledge	−0.0297**	−0.0121	−0.0803***	−0.0565**	−0.0226*	−0.0669**	−0.0210*
Risk Appetite	0.0091	−0.0014	0.0305	−0.0077	0.0156	0.0189	0.0052
Employed Member of Household	−0.0025	0.0028	−0.0132	−0.0016	−0.0050	0.0029	−0.0037
Self-Employed	0.0497***	0.0379***	0.0849***	0.0481**	0.0488***	0.0633**	0.0492***
3 Month Income Reserve	−0.0054	−0.0128*	0.0080	0.0199	−0.0144**	0.0052	−0.0091
Constant	0.1495**	0.1158*	0.2205	0.0618	0.1965***	−0.2149	0.2370***
Origination Year DVs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State DVs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,575	18,528	6,047	4,878	19,697	4,075	20,500
R-squared	0.057	0.043	0.075	0.092	0.049	0.073	0.044

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Robust standard errors omitted from table for brevity, but available upon request. The dependent variable is set to 1 if the loan entered forbearance at any point in 2020, and 0 otherwise. The sample in all models is all loans in the NMDB with a NSMO survey response that were current in December, 2019. Observation weights are normalized for the sample in column 1.

Table 6: Static Effects of Expectations on Forbearance, Models with Interactions

	Dependent Variable: Entered Forbearance in 2020				
Model	[1]	[2]	[3]	[4]	[5]
Estimator	OLS	OLS	OLS	OLS	OLS
Estimate	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$
Origination Appreciation Expectations					
Increase a lot	−0.2889***	−0.0105	−0.0022	0.0143**	0.0143**
Increase a little	−0.0736	0.0067	0.0094	0.0113**	0.0115**
Decrease a little/a lot	−0.1265	0.0256	−0.0091	0.0047	0.0051
Loan Amount (ln)	0.0035				
Increase a lot × Loan Amount (ln)	0.0248***				
Increase a little × Loan Amount (ln)	0.0071				
Decrease × Loan Amount (ln)	0.0111				
Mortgage Payment ($1000's)		0.0036			
Increase a lot × Mortgage Payment		0.0145*			
Increase a little × Mortgage Payment		0.0028			
Decrease × Mortgage Payment		−0.0139			
Married	0.0108**	0.0117**	0.0038	0.0114**	0.0114**
Increase a lot × Married			0.0245**		
Increase a little × Married			0.0033		
Decrease × Married			0.0222		
Expect Future Unemployment	0.0213***	0.0227***	0.0211***	0.0175***	0.0353***
Black	0.0424***	0.0459***	0.0412***	0.0345***	0.0412***
Expect Future Unempl × Black				0.0620*	
College Graduate					−0.0142***
Expect Future Unempl × College Grad					−0.0222*
Borrower/Loan Controls	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Origination Year DVs	Yes	Yes	Yes	Yes	Yes
State DVs	Yes	Yes	Yes	Yes	Yes
Observations	24,575	24,575	24,575	24,575	24,575
R-squared	0.122	0.122	0.123	0.128	0.122

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Robust standard errors omitted from table for brevity, but available upon request. The dependent variable is set to 1 if the loan entered forbearance at any point in 2020, and 0 otherwise. The sample in Models 1-5 is all loans in the NMDB with a NSMO survey response that were current in December, 2019. Observation weights are normalized within each of these raw samples.

Table 7: Static Effects of Expectations on Forbearance, Models with Selection

	Dependent Variable: Entered Forbearance in 2020							
Model	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Estimator	OLS	Probit	H.Probit	H.Probit	H.Probit	H.Probit	OLS	Probit
Estimate	$\hat{\beta}$	MFX	MFX	MFX	MFX	MFX	$\hat{\beta}$	MFX
Origination Appreciation Expectations								
Increase a lot	0.0344***	0.0332***	0.0387***	0.0095**	0.0147*	0.0179*	0.0173**	0.0145**
Increase a little	0.0098*	0.0103*	0.0128*	0.0014	0.0091	0.0125*	0.0120**	0.0101*
Decrease a little/lot	0.0126	0.0131	0.0164	0.0053	0.0083	0.0079	0.0052	0.0062
Expect future Unemployment	0.0223***	0.0209***	0.0243***	0.0154***	0.0200***	0.0200***	0.0202***	0.0177***
ρ			−0.175***	0.713***	−0.032	−0.155		
Borrower/Loan Controls	No	No	No	No	No	Yes	Yes	Yes
Demographic Controls	No	No	No	No	Yes	Yes	Yes	Yes
Origination Year DVs	No	No	No	Yes	Yes	Yes	Yes	Yes
State DVs	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	24,575	24,575	37,835	37,835	37,835	37,835	24,575	24,575
Selection Estimate	None	None	Log-Odds	Log-Odds	Log-Odds	Log-Odds	None	None
Origination Appreciation Expectations								
Increase a lot			−0.1987***	−0.1438***	−0.1272***	−0.1068***		
Increase a little			−0.1130***	−0.0818***	−0.0935***	−0.0699***		
Decrease a little/lot			−0.1002*	−0.0834	−0.0772	−0.0767		
Expect future Unemployment			0.0363	0.0409*	0.0454*	0.0448*		
All other controls in Main Estimate			Yes	Yes	Yes	Yes		
Interest × 2013 Origination			−0.1170***	−0.1145***	0.2669*	0.2588*		
Interest × 2014 Origination			−0.0807***	−0.0860***	0.2389*	0.2331		
Interest × 2015 Origination			−0.1415***	−0.1413***	0.1871	0.1767		
Interest × 2016 Origination			−0.1839***	−0.1907***	0.1484	0.1398		
Interest × 2017 Origination			−0.1258***	−0.1245***	0.1908	0.1916		
Interest × 2018 Origination			−0.0352	−0.0409*	0.2628*	0.2680*		
Interest × 2019 Origination			−0.1980***	−0.2011***	0.1150	0.1168		
Selection Wald χ^2			12.000	4.953	0.0275	0.428		
Selection p-value			0.001	0.026	0.868	0.513		
Non-Selected (weighted)			12,826	12,826	12,826	12,826		

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Robust standard errors omitted from table for brevity, but available upon request. The dependent variable is set to 1 if the loan entered forbearance at any point in 2020, and 0 otherwise. The sample in Models 1, 2, 7, and 8 is all loans in the NMDB with a NSMO survey response that were current in December, 2019. The sample in Models 3-6 is all loans with reported status (24,575 current plus 13,260 loans in the selection equation). Observation weights are normalized within each of these two distinct raw samples.

Table 8: Determinants of Borrower House Price Expectations at Origination

	Dependent Variable: House Price Expectations at Origination					
Model	[1]	[2]	[3]	[4]	[5]	[6]
Estimator	OLS	OLS	OLS	OLS	OLS	OLS
Estimate	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$
Network Appreciation at Origination	0.0405^{***}	0.0364^{***}	0.0263^{***}	0.0255^{***}	0.0254^{***}	0.0232^{**}
Appreciation at Origination	0.0264^{***}	0.0275^{***}	0.0253^{***}	0.0248^{***}	0.0241^{***}	0.0245^{***}
Network Unemployment Rate		0.0160^{**}	-0.0184	-0.0237^{**}	-0.0276^{**}	-0.0240
Unemployment Rate at Origination		-0.0213^{***}	-0.0204^{***}	-0.0157^{***}	-0.0127^{***}	-0.0153^{**}
Household Income (ln)				0.0659^{***}	0.0236^{***}	0.0198^{**}
Male				0.0302^{***}	0.0021	0.0123
Married				-0.0157	-0.0226^{**}	-0.0272^{**}
Age				0.0007^{**}	0.0004	0.0005
College Graduate				0.0364^{***}	0.0112	0.0227^{**}
Hispanic (any)				0.0627^{***}	0.0778^{***}	0.0802^{***}
Asian				-0.0151	0.0001	-0.0049
Black				0.0727^{***}	0.0876^{***}	0.0759^{***}
Other race/ethnicity				0.0680^{**}	0.0753^{***}	0.1116^{***}
Financial Knowledge					0.2154^{***}	0.2347^{***}
Risk Appetite					0.1347^{***}	0.1152^{***}
Employed Member of Household					0.0150	0.0223^{*}
Self-Employed					0.0085	-0.0038
3 Month Income Reserve					0.1029^{***}	0.1119^{***}
Constant	1.6953^{***}	1.7283^{***}	1.9909^{***}	1.1937^{***}	1.4614^{***}	1.4453^{***}
Origination Year DVs	No	No	Yes	Yes	Yes	Yes
State DVs	No	No	Yes	Yes	Yes	Yes
Observations	40,035	40,035	40,035	40,035	40,035	24,575
R-squared	0.039	0.041	0.054	0.060	0.072	0.080

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Standard errors are clustered at the county level and omitted from table for brevity, but available upon request. The dependent variable captures reported house price expectations in the local area at origination. The sample in Models 1-5 is all loans in the NMDB with a NSMO survey response in the 2013-2019 survey waves. The sample in Model 6 is all loans with reported current status in December, 2019. Observation weights are normalized within each of these two distinct raw samples.

Table 9: Determinants of Job Loss Expectations at Origination

	Dependent Variable: Unemployment Expectations at Origination					
Model	[1]	[2]	[3]	[4]	[5]	[6]
Estimator	OLS	OLS	OLS	OLS	OLS	OLS
Estimate	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$
Network Unemployment Rate	0.0112***	0.0102***	0.0060	0.0073	0.0091	0.0029
Unemployment Rate at Origination	0.0004	0.0007	−0.0037*	−0.0048**	−0.0056***	−0.0047*
Network Appreciation at Origination		−0.0011	0.0010	0.0012	0.0015	0.0026
Appreciation at Origination		−0.0003	0.0002	0.0002	0.0004	0.0006
Household Income (ln)				−0.0154***	−0.0047	−0.0080
Male				0.0068*	0.0154***	0.0096*
Married				0.0129***	0.0052	0.0039
Age				−0.0006***	0.0000	−0.0002
College Graduate				−0.0097**	−0.0038	0.0004
Hispanic (any)				0.0145**	0.0094	0.0129
Asian				0.0269***	0.0238***	0.0316**
Black				−0.0173**	−0.0227***	−0.0260***
Other race/ethnicity				0.0194	0.0156	0.0115
Financial Knowledge					−0.0827***	−0.0814***
Risk Appetite					0.0151*	0.0125
Employed Member of Household					0.0194***	0.0173***
Self-Employed					−0.0130**	−0.0164**
3 Month Income Reserve					−0.0644***	−0.0632***
Constant	0.0785***	0.0883***	0.1431***	0.3323***	0.2584***	0.3439***
Origination Year DVs	No	No	Yes	Yes	Yes	Yes
State DVs	No	No	Yes	Yes	Yes	Yes
Observations	40,035	40,035	40,035	40,035	40,035	24,575
R-squared	0.003	0.003	0.010	0.012	0.020	0.022

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Robust standard errors omitted from table for brevity, but available upon request. The dependent variable is set to 1 if the borrower is very or somewhat likely to face a layoff, unemployment, or forced reduction in hours in next couple of years after origination, and 0 otherwise. The sample in Models 1-5 is all loans in the NMDB with a NSMO survey response in the 2013-2019 survey waves. The sample in Model 6 is all loans with reported current status in December, 2019. Observation weights are normalized within each of these two distinct raw samples.

Table 10: Effect of Expectations on Leverage and Debt Burden

Dependent Variable:	Loan-to-Value Ratio (Col 1-3)			Debt-to-Income Ratio (Col 4-6)		
Model	[1]	[2]	[3]	[4]	[5]	[6]
Estimator	OLS	OLS	OLS	OLS	OLS	OLS
Estimate	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$
Origination Appreciation Expectations						
Increase a lot	1.2323***	0.2672	0.0980	1.2922***	1.7117***	1.6677***
Increase a little	0.4410	0.7913***	0.7327**	−0.1868	0.9336***	0.9020***
Decrease a little/lot	0.9626	1.1114	1.0940	1.0127*	0.7620	0.8778
Expect future Unemployment	−0.0874	−0.4067	−0.5882*	−0.0029	−0.2502	−0.3146
Credit Score		−0.0215***	−0.0266***		−0.0292***	−0.0296***
Enterprise Backed (vs Private)		5.5224***	4.5070***		−0.8006***	−0.6760***
Government Backed (vs Private)		19.1612***	17.5145***		2.0500***	1.9586***
National Int Rate at Origination		7.2629***	7.1408***		1.9988***	2.0119***
Rate Spread at Origination		0.5259**	0.2897		−0.0274	−0.0008
First-time home buyer		0.6010**	0.5172		−3.2328***	−3.4615***
Rate/Term Refinance		−6.3955***	−6.7738***		−0.6903***	−0.6113***
Cash-out Refinance		−7.3941***	−8.1757***		−1.5112***	−1.5555***
Household Income (ln)		2.4279***	2.4234***		−7.8862***	−7.7173***
Male		0.9377***	0.9661***		−0.0463	0.0129
Married		0.0710	−0.0710		1.4399***	1.4102***
Age		−0.2998***	−0.3064***		0.0441***	0.0413***
College Graduate		−0.1940	−0.3694		1.1172***	1.0795***
Hispanic (any)		0.6240**	1.0807***		1.0580***	1.1924***
Asian		−2.6197***	−2.1518***		1.9148***	2.1658***
Black		2.4975***	3.1450***		1.6294***	1.6618***
Other race/ethnicity		1.2544*	1.5885*		0.1357	0.0795
Financial Knowledge		−0.6250	−1.3024**		1.7743***	1.7961***
Risk Appetite		−0.5086	−0.4557		1.0037***	1.0100***
Employed Member of Household		0.3581*	0.3678		0.6532***	0.6806***
Self-Employed		−1.4542***	−1.3311***		2.2287***	2.1278***
3 Month Income Reserve		−2.9540***	−2.5825***		−0.9755***	−1.0810***
Constant	79.3261***	52.0275***	61.0125***	33.9977***	130.6874***	129.4349***
Origination Year DVs	Yes	Yes	Yes	Yes	Yes	Yes
State DVs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,035	40,035	24,575	40,035	40,035	24,575
R-squared	0.035	0.380	0.388	0.019	0.221	0.214

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Robust standard errors omitted from table for brevity, but available upon request. The dependent variable in Models 1-3 is LTV and the dependent variable in Models 4-6 is DTI. The sample in Models 1, 2, 4, and 5 is all loans in the NMDB with a NSMO survey response in the 2013-2019 survey waves. The sample in Models 3 and 6 is all loans in the NMDB with a NSMO survey response that were current in December, 2019. Observation weights are normalized within each of these two distinct raw samples.

Appendix

A.1 Supplement to Data and Measurement

Particularly as we are among the first to begin using these survey data for research, we now summarize the main variables of interest and their definitions for clarity and future research. Several variables incorporated in this analysis are derived from survey responses compiled from 30 waves of the National Survey of Mortgage Originations (NSMO). The exact question numbers in different survey waves varied slightly, but the reference to any question number in this analysis is based on the numbering in NSMO survey waves 29 and 30, which includes the most recent printing of the survey as of the publishing of this analysis. We have the following variables as controls in our main specification:

Expected Unemployment *(Source: National Survey of Mortgage Originations)*: **NSMO Question 95c** asks: *How likely is it that in the next couple of years you (or your spouse/partner) will face a layoff, unemployment, or forced reduction in hours?* Possible answers to this question are, *Very, Somewhat, Not at All.* The binary **Expected Unemployment** variable takes a value of 1 when the respondent selects *Very* or *Somewhat* and 0 otherwise.

Financial Knowledge *(Source: National Survey of Mortgage Originations)*: Respondents are asked a series of questions regarding their financial knowledge both 1) prior to beginning the mortgage origination process (**NSMO Question 05**) and 2) after they completed the origination process (**NSMO Question 56**).

> **NSMO Question 05** asks: *When you began the process of getting this mortgage, how familiar were you (and any cosigners) with each of the following:*
>
> b) The different types of mortgages available.
>
> c) The mortgage process.
>
> d) The down payment required to qualify for a mortgage.
>
> e) The income required to qualify for a mortgage.

e) Your credit history or credit score.

g) The money needed at closing.

NSMO Question 56 asks: *How well could you explain to someone the...*

a) Process of taking out a mortgage.

b) Difference between a fixed- and adjustable-rate mortgage.

c) Difference between a prime and a subprime loan.

d) Difference between a mortgage interest rate and its APR.

e) Amortization of a loan.

Possible answers to each of these questions are, *Very, Somewhat, Not at All.*

The **Financial Knowledge** variable is an equally weighted linear combination of the responses to these two series of questions, with a *Very* response receiving 2 points, a *Somewhat* response receiving 1 point, and a *Not at All* response receiving 0 points. Therefore, a respondent with all *Very* responses would have a maximum **Financial Knowledge** score of 22 and a respondent with all *Not at All* responses would have a minimum **Financial Knowledge** score of 0.

Financial Risk Tolerance *(Source: National Survey of Mortgage Originations)*: **NSMO Question 89** asks: *Which one of the following statements best describes the amount of risk you are willing to take when you save or make investments?* Possible answers to this question are, *Take substantial financial risks expecting to earn substantial returns, Take above-average financial risks expecting to earn above-average returns, Take average financial risks expecting to earn average returns, Not willing to take financial risks.* The binary **Risk Appetite** variable takes a value of 1 when the respondent selects *Take substantial financial risks...* or *Take above-average financial risks...* and 0 otherwise.

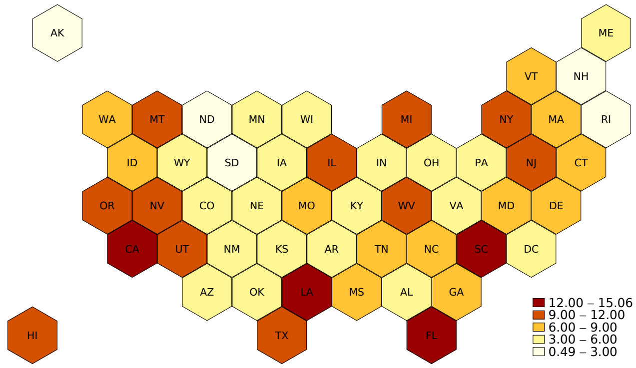
3-month Income Cushion *(Source: National Survey of Mortgage Originations)*: **NSMO Question 96a** asks: *If your household faced an unexpected personal financial crisis in the next couple of years, how likely is it you could pay your bills for the next 3 months without borrowing?* Possible answers to this question are, *Very, Somewhat, Not at All.* The binary **3 Month Income Reserve** variable takes a value of 1 when the respondent selects *Very* or *Somewhat* and 0 otherwise.

To better understand the spatial heterogeneity in forbearance rates and their relationship with expectations across states, Figure A.1 provides a heat map. Starting with Panel (a), some states, such the Dakotas and upper New England, had very low rates of forbearance, at below 3%, whereas others, such as California and Florida, had high rates between 12-15%. One potential explanation behind this pattern is the response to the pandemic: whereas some states had very severe restrictions, which may have worsened the employment decline (and thus ability to pay), other states responded less severely. However, still, there is important heterogeneity, as demonstrated by Florida, which had a high rate of forbearance despite not having severe lock downs. These settings appear to be driven in large part by their industry composition—that is, Florida's high concentration of leisure and hospitality jobs, which were especially depressed, relative to trend, over the pandemic.

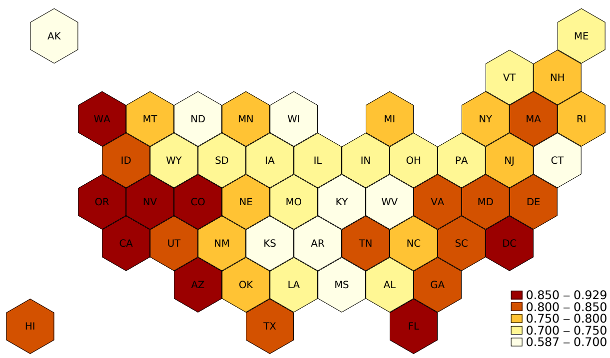
Turning to Panels (b) and (c), we see similarly large heterogeneity, spanning from 58% to 93% of respondents who anticipate positive house price growth in some states and 5.2% to 23% of respondents who anticipate future unemployment in other states. Some states, like Colorado, exhibit both optimism about house prices and pessimism about the labor market, whereas other states, like Arizona, expect high house price growth and low future unemployment. Given the differential exposure to the pandemic across space and the share of jobs that could be done remotely, this cross-sectional variation is important for identification.

Figure A.1: Spatial Distribution of Beliefs and Forbearance

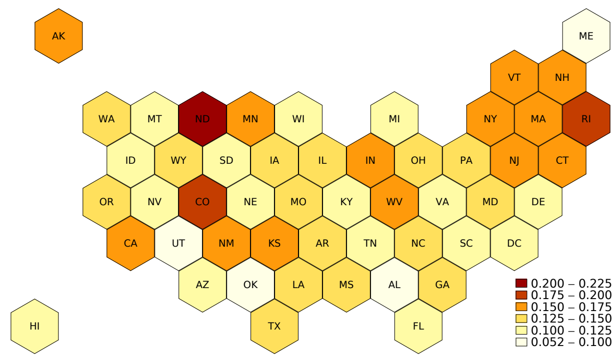
(a) Share in Forbearance in 2020



(b) Share Who Expect Positive Appreciation



(c) Share Who Expect Future Unemployment



Sources: National Mortgage Database and National Survey of Mortgage Originations.
Notes: The figures present: panel (a), shares of loans in the NMDB with a NSMO survey response that were current in December 2019 and entered forbearance at any point in 2020; panel (b), the share of borrowers who responded to question 69 in the survey, *What do you think will happen to the prices of homes in this neighborhood over the next couple of years* with *Increase a lot* or *Increase a little*; and panel (c), the share of borrowers who responded to question 95c in the survey, *How likely is it in the next couple of years that you or your spouse will face...a layoff, unemployment, or a forced reduction in hours*, with *somewhat likely* or *very likely*.

Table A.1: Forbearance Rates by Updated and Resolved Expectations, Robustness

	Dependent Variable: Forbearance in month t			
Model	[1]	[2]	[3]	[4]
Estimator	OLS	OLS	OLS	OLS
Estimate	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$
$e^h_{i\tau} \times e^{hN-}_t$	-0.0292^{**}	-0.0510^{***}		-0.0372
	[0.0114]	[0.0175]		[0.0230]
$e^h_{i\tau} \times e^{hN+}_t$			-0.0340^{***}	-0.0175
			[0.0119]	[0.0170]
$e^h_{i\tau} \times \Delta p_{ct}$	-0.0259^{***}	-0.0671^{***}		
	[0.00740]	[0.0187]		
$e^u_{i\tau} \times u_{ct}$	0.0767^{***}	0.157^{***}	0.154^{***}	0.154^{***}
	[0.0270]	[0.0505]	[0.0504]	[0.0505]
$e^{h++}_{i\tau} \times e^{hN-}_t$		-0.0112		
		[0.0206]		
$e^h_{i\tau} \times \Delta p_{ct}$		-0.0006		
		[0.0256]		
$f_{i,t-1}$	0.715^{***}			
	[0.00414]			
Borrower FE	Yes	Yes	Yes	Yes
Time period FE	Yes	Yes	Yes	Yes
Observations	390,762	390,762	390,762	390,762
R-squared	0.766	0.49	0.49	0.49
Clusters	20,879	23,581	23,581	23,581

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Standard errors, clustered by borrower, in brackets. The dependent variable is forbearance status as of month t. This is estimated as a function of individual and time period fixed effects, and interactions of NSMO survey responses at origination interacted with COVID-era beliefs and economic outcomes. The model is estimated over monthly data from January 2020 through January 2022.

Definitions: $e^h_{i\tau}$, NSMO house price expectations at origination either "up a little" or "up a lot" in the "next couple of years"; $e^{h++}_{i\tau}$, NSMO house price expectations at origination "up a lot" in the "next couple of years"; $e^{hN-}_t = 1 - s_t$, where s_t fraction of households responding to question 46 of the Michigan Survey of Consumers as "decline" in the next 12 months; e^{hN+}_t, the fraction of households responding to question 46 of the Michigan Survey of Consumers as "increase" in the next 12 months; Δp_{ct}, the year-on-year log-difference in the county home value index from Zillow; u_{ct}, the county-level unemployment rate from the Bureau of Labor Statistics.

Table A.2: Determinants of House Price Expectations at Origination, Ordered Logit Models

	Dependent Variable: House Price Expectations at Origination					
Model	[1]	[2]	[3]	[4]	[5]	[6]
Estimator	O.Logit	O.Logit	O.Logit	O.Logit	O.Logit	O.Logit
Estimate	Log Odds	Log Odds	Log Odds	Log Odds	Log Odds	Log Odds
Network Appreciation at Origination	0.1253***	0.1161***	0.0776***	0.0769***	0.0768***	0.0712***
Appreciation at Origination	0.0757***	0.0791***	0.0731***	0.0715***	0.0697***	0.0729***
Network Unemployment Rate		0.0527***	−0.0537*	−0.0687**	−0.0796**	−0.0653
Unemployment Rate at Origination		−0.0652***	−0.0628***	−0.0500***	−0.0417***	−0.0504***
Household Income (ln)				0.1848***	0.0634***	0.0520*
Male				0.0921***	0.0090	0.0426
Married				−0.0521*	−0.0719**	−0.0832**
Age				0.0020**	0.0011	0.0011
College Graduate				0.1075***	0.0341	0.0676**
Hispanic (any)				0.2253***	0.2701***	0.2771***
Asian				−0.0307	0.0137	−0.0074
Black				0.2801***	0.3258***	0.2851***
Other race/ethnicity				0.2112***	0.2342***	0.3445***
Financial Knowledge					0.6323***	0.7021***
Risk Appetite					0.4141***	0.3518***
Employed Member of Household					0.0411	0.0623*
Self-Employed					0.0240	−0.0142
3 Month Income Reserve					0.2822***	0.3169***
cut1	−2.7550***	−2.8272***	−3.6899***	−1.4624***	−2.2502***	−2.2702***
cut2	−0.5966***	−0.6666***	−1.5180***	0.7173**	−0.0559	0.0313
cut3	2.2412***	2.1752***	1.3618***	3.6135***	2.8686***	2.9619***
Origination Year DVs	No	No	Yes	Yes	Yes	Yes
State DVs	No	No	Yes	Yes	Yes	Yes
Observations	40,035	40,035	40,035	40,035	40,035	24,575

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Standard errors are clustered at the county level and omitted from table for brevity, but available upon request. The dependent variable captures the increasing ordered levels of reported house price expectations in the local area at origination: *Decrease a little/lot, Increase a little, and Increase a lot*, all relative to *Remain about the same*. The sample in Models 1-5 is all loans in the NMDB with a NSMO survey response in the 2013-2019 survey waves. The sample in Model 6 is all loans with reported current status in December, 2019. Observations weights are normalized within each of these two distinct raw samples.